COGNITIVE PROBING FOR AUTOMATED NEUROADAPTATION

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ABSTRACT: The concept of *cognitive probing* is presented as a method for a computer system to autonomously gather information about a user's preferences. This is demonstrated using a form of cursor control.

INTRODUCTION

Neuroadaptive technology uses measures of its user's neurophysiological activity in order to enable and inform its own adaptation to that user [1]. As such, a goal-directed closed feedback loop can be created where the user state induces system adaptations, and system adaptations influence the user state [2]. Such a system must then also have a goal or "agenda" to guide its adaptations [3]. For example, adaptive automation systems increase automation levels when a user's workload is high and vice versa [4-5]. Their goal is to balance workload such that an optimal level of engagement is maintained. The logic to reach this goal, however, is generally pre-programmed: the adaptive responses to different levels of workload are fixed. Furthermore, the closed-loop adaptation limits the possibilities of adaptation to the information that is present within that loop—in this case, the one-dimensional measure of workload can only have a one-dimensional response of automation levels. *Cognitive probing* represents a way to a) automatically learn which adaptations are effective in which contexts with only limited prior logic, and b) go beyond closed-loop adaptation to *automated adaptation*: the automatically gathered information can be used by the system to act autonomously, outside of any ongoing control loop, in order to achieve or pursue any number of different goals. A cognitive probe is an adaptation initiated by the system in order to gauge the user's response to it. The responses to different adaptations are registered along with their contexts in a user model. With an increased number of context-probe-response samples, the model increasingly accurately describes various aspects of the user's (cognitive) behaviour, such as preferences and goals. It is these inferred, higher-level preferences and goals, finally, that form the basis of user-supportive adaptations—not merely the current context and neurophysiology.

MATERIALS AND METHODS

In a cursor control task, the cursor was autonomously controlled by the system. Probes consisted of cursor movements into random directions. Movements were restricted to a grid with up to eight possible directions. EEG was recorded from 19 participants passively observing these movements. The responses recorded from the EEG represented approval or rejection of the observed movement. This signal was automatically induced by the cursor movements and not consciously modulated. After a number of probes, the user model thus contained information concerning the preferred direction of movement. The system could now guide the cursor towards the correct direction. See [1] for details.

RESULTS

Figure 1 displays the average improvement in cursor performance. The system did not know where the user-intended target was, and the user did not know it had any influence on the system-controlled cursor. However, using automated neuroadaptation, the cursor effectively found its way to the target.

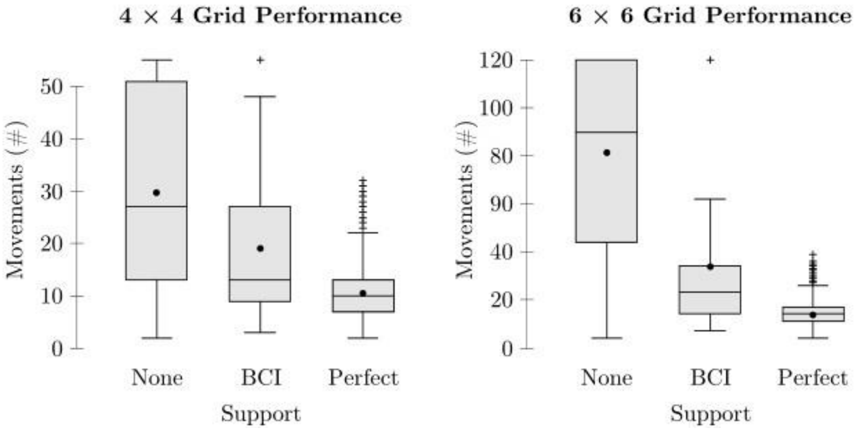

Figure 1: Cursor performance on two different grid sizes. 'Random' indicates cursor performance without neuroadaptation, 'online' with neuroadaptation, and 'perfectly reinforced' is the theoretically optimal performance given the constraints of the paradigm.

CONCLUSION

We have demonstrated a system that automatically 'probes' for information in order to learn and adapt to its user's preferences, without the users being aware of these preferences being transmitted

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